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How to improve learners' (mis) understanding of CO_2 accumulations through the use of human-facilitated interactive learning environments?

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ABSTRACT

On a global scale, the need for CO2 mitigation and adaptation strategies is both compelling and urgent. While there are several challenges including political, economic, and technological, IPPC has identified the lack of mitigation and adaptation strategies and the lack of "flows of knowledge and information relevant for adaptation decisions" as the fundamental barriers to adaptation. In fact, there exists much scientific evidence of how environmental emissions (e.g., CO2) are contributing to the global warming and climate change phenomena, yet subjects in numerous experimental studies show a poor understanding of, and engagement with, environmental accumulations. How can learners' understanding of environmental accumulations be improved? We argue that the adoption of the stock and flow perspective, which provides effective tools such as System Dynamics based Interactive Learning Environments (SDILEs) for education and engagement can address this challenge effectively. In our experiments, we assessed the impact of three interventions and found that education and training with human-facilitated SDILE improved learners' understanding of, and ability to apply, the basic principle of accumulation much more than of those who were trained only with standalone SDILE or those who had a traditional lecture-based session. Such an improved understanding about CO2 accumulation is expected to support the design and implementation of mitigation and adaptation strategies needed for our sustainable future.

1. Introduction

Most people don't deny the detrimental effects (e.g., atmospheric warming (Wu and Lee, 2015), sea-level rise, and increasing extinction rates (Weber, 2013; Eisenack et al., 2014) of environmental emissions (Myers et al., 2013; Vikhorev et al., 2013). However, when it comes to the management and control of these environmental emissions, the situation is not encouraging (Cronin et al., 2009; Sterman and Sweeney, 2007). With the passing of each day, more fossils are burnt and fewer trees are planted: (i) researchers have estimated that over 15 billion trees are cut down each year, and the global number of trees has fallen by approximately 46% since the start of human civilization (Crowther et al., 2015), and (ii) over the past two decades the global consumption of fossils continues to show an increasing trend (BP, 2015). Consequently, CO_2 concentration in the atmosphere is increasing which is considered as the single most important factor contributing to global warming (Lacis et al., 2010). Therefore, on a global scale, the need for CO_2 mitigation and adaptation strategies is both compelling and timely. While there are several challenges, (e.g., political, economic, and technological) the lack of mitigation and adaptation strategies and the lack of "flows of knowledge and information relevant for adaptation decisions" are fundamental barriers to adaptation (IPPC, 2007). Consistent with IPPC's findings, various experimental studies show that subjects lack basic knowledge about environmental accumulations. For instance, they can't differentiate between a stock (i.e. accumulation) and its flows or they did not grasp the casual relationship between a stock and its flows (Cronin et al., 2009; Itkonen, 2015). The basic understanding about the concepts of stock and flow is essential for all decision makers, be it at a public, private, or personal level. For example, public officials are charged with effective and efficient

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management of national resources such as fisheries and other resource stocks. In business organizations, managers have to manage the stocks of inventory and production capital. At a personal level, majority of the people have to deal with the stock of "wealth". On the one hand, the concepts of stock and flow are easy to understand - any resource (a stock) accumulates or depletes and its flows change it (Cronin et al., 2009). For instance, to accumulate wealth (a stock) one needs to have more income (an inflow) than expenditure (an outflow) over time, or a garbage dump (a stock) will continue to rise if more garbage is added (an inflow) than is removed (an outflow), or to maintain a sustainable stock of fisheries, we can't afford overharvesting (i.e., a negative net flow when an outflow, in this case the harvesting rate, is greater than an inflow, or else the generation (birth) rate, the stock (of fisheries) will continue to decline and even can go extinct. On the other hand, the research has shown time and time again that subjects in experimental studies do not sufficiently understand the difference between stocks and flows. For instance, they cannot track the behavior of even a single stock when they are provided with complete information about this stock's inflow(s) and outflow(s) (Sterman, 2000). These subjects who are our adult learners in STEM and business subjects at post-secondary levels soon will be seeking careers in public and private sectors. Some of them will be charged with the management of renewable and non-renewable resources where we can't afford such poor understanding about the basic dynamics of stocks and flows. For instance, poor understanding of basic dynamics of many renewable resources such as fish and whales, forests, soil, and ground water reservoirs has often resulted in overexploitation and at times, extinction (Moxnes, 2004, 2005).

In the case of global warming, many people believe its effects will be gradual and we have plenty of time to act. They reason that there is little evidence of warming so far, and even less evidence of its harmful effects. Some perceive climate change as a problem distant in time and space (Myers et al., 2013; Islam et al., 2016; Sun et al., 2016). It is better to wait and see - if global warming turns out to be greater and more harmful than expected, policies to mitigate it can then be pursued, they argue (Sterman, 2010). However, when there are long delays between actions and their consequences, as is the case with global warming and climate change, mitigating the risks therefore requires environmental emission reductions long before additional harm is evident (Sterman, 2008).

To improve learners' decision making in such dynamic tasks as the management of environmental accumulations, the development and the use of simulation-based games has been on the rise since the advent of modern computing technologies (Faria, 1998; Mayer et al., 2011; Tamara et al., 2013). Specifically, system dynamics (Forrester, 1961) simulation-based interactive learning environments (SDILEs), as a decision support system tool, are purported to be an effective training tool for dynamic tasks. Yet, the effectiveness of these SDILEs in improving people's decision making is limited (Qudrat-Ullah, 2007, 2014a; Lee et al., 2012).

One way to improve the effectiveness of these decision support systems is to incorporate structured debriefing. Structured debriefing is an after-the-simulation-experience human-facilitated activity that allows the decision makers to share, evaluate and reflect on their decision making experiences with the SDILE (Ledrman, 1992; Qudrat-Ullah, 2014a). Specifically, the task structures (e.g., stocks and flows) which are responsible for the outcome (e.g., rise or fall in CO_2 emissions stock) are elaborated on during these human-facilitated debriefing sessions. Better understanding and learning about the task system is critical to the promotion of adaptive behavior for the decision makers (Tarnoczi, 2011).

An improved understating of the task structures leads to improved performance in dynamic tasks (Alessi and Kopainsky, 2015). Although prior research has shown positive effect of debriefing–based simulation training, its implementation requires structured, intensive and formal teaching of system dynamics (Sterman, 2010; Pavlov et al., 2015). Granted that these solutions are effective, but they are both time intensive and prohibitively expensive. Not many organizations can afford to send their decision makers to formal education in system dynamics. To overcome such a challenge, we propose the incorporation of human-facilitation into the design of SDILEs based training workshops, focused on the elaboration of the accumulation principle: that the state of a stock (level) can only be controlled through its flows (rates) or only the net flow (i.e. (outflows-inflows)) can cause an increase (or decrease) into a stock, as an alternate, innovative and cost-effective solution. When people understand the dynamics of accumulation processes underlying a dynamic task, their performance (e.g., task of stabilizing CO_2 emissions at a certain level) improves (Sterman, 2000; Qudrat-Ullah, 2014a). Therefore, we will investigate the research questions: 'Does training, in a workshop setting, with SDILEs, improve subjects' understating of environmental accumulations?'; and 'For a better understanding of the environmental accumulations, is training with a human-facilitated SDILE better than training with a standalone SDILE?'

First, we provide a brief overview of the widespread existence of public misunderstanding of accumulations. When people, otherwise well-educated and experienced, perform poorly in even simple one stock, one inflow and one outflow based tasks, the need for understanding the basic dynamics of accumulations becomes even more pronounced. To overcome the misunderstanding about environmental accumulations, we suggest training with human-facilitated SDILEs as a viable solution. Then, we provide empirical evidence to the effectiveness of this proposed solution—training with human-facilitated SDILEs. We conclude that for better understanding and management of CO_2's unabated accumulations, decision makers should embrace the stock and flow perspective.

2. Literature review

While the nature of environmental accumulations is complex, the essence of the problem is as simple as filling a bathtub. The stock of water in a tub is increased by the inflow (i.e. by opening the faucet) and is decreased by outflow (i.e. by opening the drain). Now if people are given information on both the inflow and outflow, it is fairly easy to depict the trajectory of the stock - how water is accumulated in the tub. However, several studies using this task and other problems involving a single stock and two flows found that the average performance was less than 50% of the optimum (Steiner and Posch, 2006; Alessi and Kopainsky, 2015; Qudrat-Ullah, 2010). Why does this happen? Prior research has identified the poor understanding of the basic principle of accumulation processes that any change in a stock (in our case, the increase or decrease of CO_2 concentrations in the atmosphere) is dependent on its inflows (all additions) and outflows (all reductions)) (Cronin et al., 2009; Qudrat-Ullah, 2014b; Itokonen, 2015). This empirical evidence is a fine illustration of the power of understating the basic dynamics of complex systems in terms of stocks and flows. Thus, the stock and flow perspective on environmental emissions informs us that stabilizing CO_2 emissions near current rates is not going to stabilize the global climate, but ensures higher CO_2 concentrations and continued global warming. Understanding the basic dynamics (i.e. the stocks and flows nature) of environmental accumulations is indeed a pre-requisite

of any adaptive change expected from the public (Kikuchi-Uehara et al., 2016).

When it comes to improving decision makers' ability to better understand the dynamics of accumulation-based tasks, a formal education in systems dynamics is an effective solution (Sterman, 2010). However, for most of the business organizations, sending their employees for a semester-long education and training in system dynamics is hardly a feasible option, both in terms of money and time. Therefore, SDILEs-based training sessions, in a workshop setting, are expected to provide a relatively low-cost and effective solution to this managerial decision aiding need.

While system dynamics models have long served decision makers in the global warming and climate change domain (see Table 1), their use as a training and educational tool for the management and control of environmental emissions have only recently started (Sterman, 2010; Saysel and Hekimoğlu, 2013). The debriefing-based SDILEs are considered effective tools for the education, training and engagement of people with dynamic issues including environmental accumulations (Qudrat-Ullah, 2014b; Babin et al., 2009; Puustinen; Rouet, 2009). An SDILE has three components (i) a system dynamics based computer simulation model to adequately represent the problem, (ii) a user interface that enables decision makers to make decisions and access the feedback on an interactive basis, and (iii) a human facilitator for conducting briefing and debriefing sessions (Qudrat-Ullah, 2007; Pavlov et al., 2015). Some researchers have used automated, instead of human facilitation in their SDILEs, (Alessi and Kopainsky, 2015; Qudrat-Ullah and Karakul, 2007; Stavredes, 2001). However, in the absence of human-facilitation, the decision makers, after they have the rich learning experiences with simulation-based decision support systems, face difficulty in clarifying some misconceptions about the task system (e.g., why decreasing the inflow of CO_2 emissions did not stop the rise in CO_2 accumulations) (Ledrman, 1992; Sterman, 2010; Qudrat-Ullah, 2014b). Moreover, there are many experiences that the decision-makers can have while learning with decision support systems. They initially have no way of knowing which are important and useful in the real world (Lane, 1995; Qudrat-Ullah et al., 1997). Provision of both positive and negative feedback on subjects' actions is critical (Sanden and Karlstrom, 2007). Human facilitation may provide this knowledge and hence may aid in the development of expertise.

Some examples of SDILEs are People's Express (Repenning and Sterman, 2002) FishBankILE (Qudrat-Ullah et al., 1997), Healthcare Microworld (Hirsch and Sherry, 1999), C-Roads (C.R., 2015), and C-Learn (C. I., 2015). The basic premise of an SDILE is that by understanding the structure of a system (e.g., the stocks and flows of our resource consumption system) one can manage the behavior of the system (e.g., trajectory of environmental accumulations) – the stock and flow thinking. The SDILEs promote experiential learning - *learning by doing*. With such a promising potential, the training with SDILEs should improve learners' decision making and learning in dynamic tasks. Our interest here in this investigation, therefore, is to empirically test the effectiveness of SDILEs in improving learners' understanding of the basic dynamics of environmental emissions. Specifically, we will test the following hypotheses:

H1. Subjects trained with a human-facilitated SDILE will better understand the dynamics of environmental accumulations than those trained with a standalone, automated SDILE.

H1a. Subjects trained with a standalone, automated SDILE will better understand the dynamics of environmental accumulations than those without any SDILE.

H1b. Subjects trained with a human-facilitated SDILE will better understand the dynamics of environmental accumulations than those without any SDILE.

Table 1
Sources of some system dynamics models related to various global warming and climate change issues are listed.

Model use area	Sources
Global warming	Sterman and Sweeney, 2007; Naill et al., 1992; Fiddaman, 2007; Sterman, 2002; Saswinadi and Muhammad, 1991; C.1., 2015; Saysel and Hekimoğlu, 2013
Climate Change	Ulli-Beer et al., 2010; Fiddaman, 2002; Bastian et al. 2013; Jeon et al., 2015; Jiao et al., 2014; Guo and Guo, 2015; Qudrat-Ullah, 2015, 2014, 2013

3. Methods

To test our hypothesis on the effectiveness of human-facilitated SDILEs in improving decision making about environmental accumulations, we employed the laboratory-based experimental method. To test our hypotheses, we applied three criteria to select our methodology. First, the experimental setting was a computer simulation-based laboratory. This experimental approach is advantageous in the study of decision making in dynamic tasks such as the environmental accumulation task. In such tasks, much of the task complexity is the result of the interaction among the flow of information, actions, and consequences during the performance of the task (Qudrat-Ullah, 2014; Sterman, 1994). For instance, there are time lags between actions and their consequences which may make learning very difficult. On the other hand, the use of SDILEs allows for compressing these dynamics, thereby facilitating successful learning (Sterman, 2000). Second, we wanted our hypotheses to be testable across interventions (facilitation types: human versus automatic). Therefore, we used two facilitation types (human versus automatic) in the design of SDILEs. Finally, our subjects should be real decision makers or have had sufficient training in managerial decision making.

The issue of the generalizability of the results can be a potential limitation of the laboratory experimentation method. On the other hand, the laboratory experimentation is an established method of scientific inquiry within psychology and organizational behavior literature and provides an authentic enactive mastery experience for decision makers (Moxnes, 2004; Qudrat-Ullah, 2014b). According to Locke, there are remarkable similarities between research findings obtained in laboratory experimental method and field settings (Locke, 1986). The use of students as participants can also raise the question of the generalizability of the results. However, several studies in the domain of dynamic decision making (e.g., Moxnes, 2005; Qudrat-Ullah, 2014a) have used student participants based on the general conclusion that the formal properties of dynamic tasks are much more important determinants of decision making performance than participant profiles (Ashton and Kramer, 1980).

3.1. The experimental design

In our experiment, we used a three-groups (i.e. G1, G2, and G3) pretest-treatment-posttest research design in which the intervention was the two SDILEs (i.e. with and without human facilitation). The group G1 had no SDILE, group G2 had human-facilitated SDILE, and group G3 had automated-facilitated SDILE.

Table 2
The experimental procedures.

Step	Activity
1	**Greeting, Introducing the Steps Below, and Pre-Treatment Testing** - Greeted by the investigator - Signed the consent form - Briefing about the experimental sessions. - Encouraged to ask questions, if any. - Assigned to an available computer - Answered the pre-treatment task, T1 - Assigned with an anonymous ID indicating the treatment groups, G1, G2, and G3
2	**Treatment Sessions** - Went through the computer screens for the training session - Directed to the practice trial at the last screen of the training session - Told that score for practice trial not counted - Started the two formal trials following the practice trial - Participated in the debriefing sessions - Directed to proceed to post-treatment testing
3	**Post-Treatment Testing** - Geeted by the investigator - Accomplished the post-treatment task, T2 - Directed to collect the payment - Left the room with a note about further contact information to know the results of this study

3.2. Participants and experimental settings

Data for this study was collected from voluntarily recruited post-graduate students of a large Swiss private university through an open university-wide bulletin boards-based advertisement. Table 2 lists the experimental procedures. A total of 105 participants signed up but only 99 of them completed the experiment. A total of 33 subjects were randomly assigned to each of the three experimental conditions (i.e. G1, G2, and G3) on the same day, and were not told that different experimental conditions were being tested. They were not allowed to interact and on their arrival to assigned lab rooms, they signed the consent form, completed the demographic questionnaire and received the briefing about their tasks.

3.3. Pre-treatment testing

In this pretest-intervention-posttest research design, all subjects completed the "prior knowledge task", Task1, a modified version of "pollution in a pond" task (Stave et al., 2014) as shown in Fig. 1. Task 1 had two parts: part one was to draw, based on "added" and "removal" information about the pollutant per day, the resulting path of the stocks of pollutants over a period of 30 days,

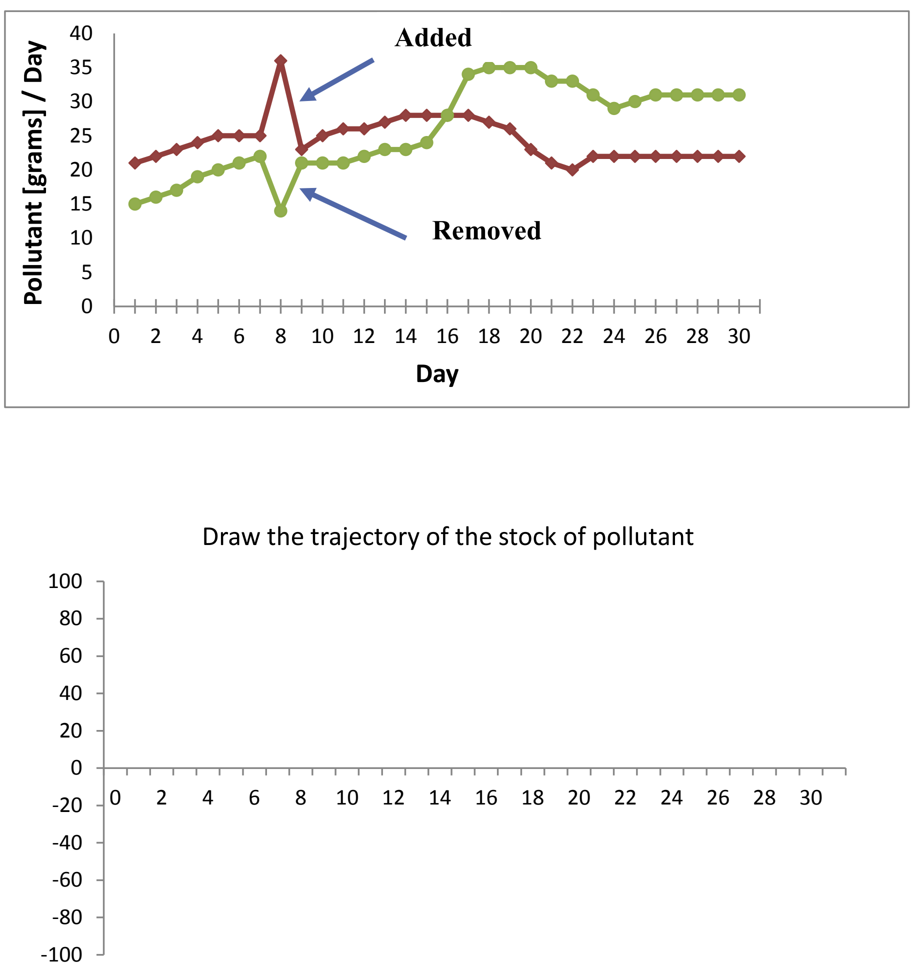

Fig. 1. Pollution in a pond task (Task 1).

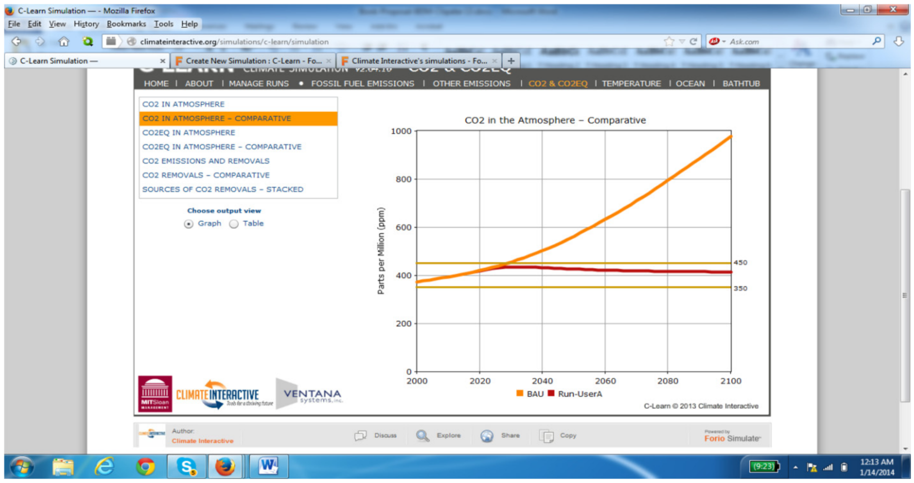

Fig. 2. CO_2 in the atmosphere by User-A (adopted from Qudrat-Ullah (2014)).

and part 2 was to answer the following four questions (Stave et al., 2014): (1) On what day (from day 1 to day 30) was the most pollutant added, (2) On what day was the most pollutant removed (3) When (i.e. on which day), was the most pollutant in the pond, and (4) On what day was the least pollutant in the pond?

3.4. Treatments: lecture-based, human-facilitated SDILE-based, and auto-facilitated SDILE-based education and training on "CO_2 emissions stabilization task"

After doing the pre-treatment task, Task 1, while the participants of G1, with no SDILE, attended a 2-h case-based lecture on environmental sustainability, those with SDILEs, G2 and G3, proceeded to perform learning and training with a C-Learn simulator (C.I., 2015). G1 went through a traditional case-based lecture for 2 h where the case, "Making the Business Case for Environmental Sustainability (Henderson, 2015)," was at the center of discussion. In this session, the crux of the arguments was around the assertion that the reduction of CO_2 emissions reduces the risk of climate change.

Participants in G2 were briefed by a trained human facilitator about the C-Learn learning environment and how to use it to learn about environmental accumulations. G3 availed the scripted, automated briefing facility. Both groups were encouraged to design a policy, based on the decision parameters available in C-Learn that will stabilize CO_2 emissions. In this publicly available climate change-based interactive learning environment, C-Learn, subjects were given the opportunity to go through a scientific method of learning (i) form hypotheses/make decisions (e.g. how much to remove):, (ii) test the hypotheses, (iii) instantly receive feedback and (iv) repeat the process as many times as they wished. All participants, after their session with C-Learn, were debriefed.

3.4.1. Debriefing design

After practicing with C-Learn, a SDILE, debriefing was designed to provide the subjects opportunities to reflect and learn. For instance, those in G2 were shown their performance graphs that were automatically recorded by the C-Learn simulator (e.g., see in Fig. 2 the performance of a user). In Fig. 2, compared with a business as usual (BAU) scenario, User-A was able to stabilize CO_2 concentrations in the range of 350–450 parts per million. C-Learn allows the user to see their performance both in graphical as well as in tabular form.

In the human-facilitated SDILE group, G2, not only what happened, but also why it happened, was shared and reflected upon. For G3, the automated facility had multiple choice questions and their answers to facilitate their debriefing session. This debriefing activity also served the purpose of "de-immersion" for the groups G2, and G3 who had the sessions with C-Learn, a simulation-based learning environment.

3.5. Post-treatment-testing

In the final phase of the study, all subjects were asked to complete an environmental accumulations task, Task 2. For Task 2, we used Sterman's CO_2 emissions task (Sterman, 2008). Subjects were provided with the task description about the stock of atmospheric CO_2 emissions, and the removal of CO_2 from the atmosphere by natural resources They received the two CO_2 evolution scenarios in which atmospheric CO_2 gradually rises (or falls) from year 2000 level of about 370 ppm–400 (340) ppm by 2100, with changes of roughly ± 8%, exactly the same as Sterman did (for a detailed task description, see Sterman's work (Sterman, 2008)). Here, subjects were to (i) draw the trajectory of flows corresponding to the evolution of CO_2 concentration and (ii) answer questions related to CO_2 flows and accumulation – an analogous task to Task 1. Subjects in G1, after they completed Task 2, were also encouraged to learn and train with the automated self-contained SDILE.

Overall, in this study, the novelty from the viewpoint of methodology in the area of learning and education is in the design, development, and testing of a structured human-facilitation based ILE to improve users' decision making in dynamic tasks. This design innovation stems from the systematic integration of system dynamics (Forrestor, 1961), learning principles (Bloom, 1956; Ledrman, 1992), and dynamic decision making (Sterman, 2000).

4. Results

The first step was to assess the participant's background demographics and prior knowledge about environmental accumulations. The demographic statistical analysis, given in Table 3, shows that all three groups were comparable in age (average age was 28.7 years), gender (61% were male and the rest were female), academic background (35% in STEM, 45% in business, economics and management and 20% were in humanities), and work experience (over

Table 3
Participants' demographics.

Variable	Control Group, G1 (without SDILE)	Experimental Group, G2 (human-facilitated SDILE)	Experimental Group, G3 (Auto-facilitated SDILE)	Test Statistic	P-value
n	33	33	33		
Age	28.7 (1.4)	28.6 (2.1)	28.8 (1.6)	F = 0.08	p > 0.05
Gender	61%			$\chi^2 = 0.49$	p > 0.05
Male	39%				
Female					
Academic Background	11	12	11	F = 0.07	p > 0.05
STEM	15	14	15		
BEM	7	7	7		
Humanities					
Work Experience	3.2 (0.52)	3.0 (0.46)	3.1 (0.41)	F = 0.03	p > 0.05

NOTE: Values in parentheses are standard deviations.

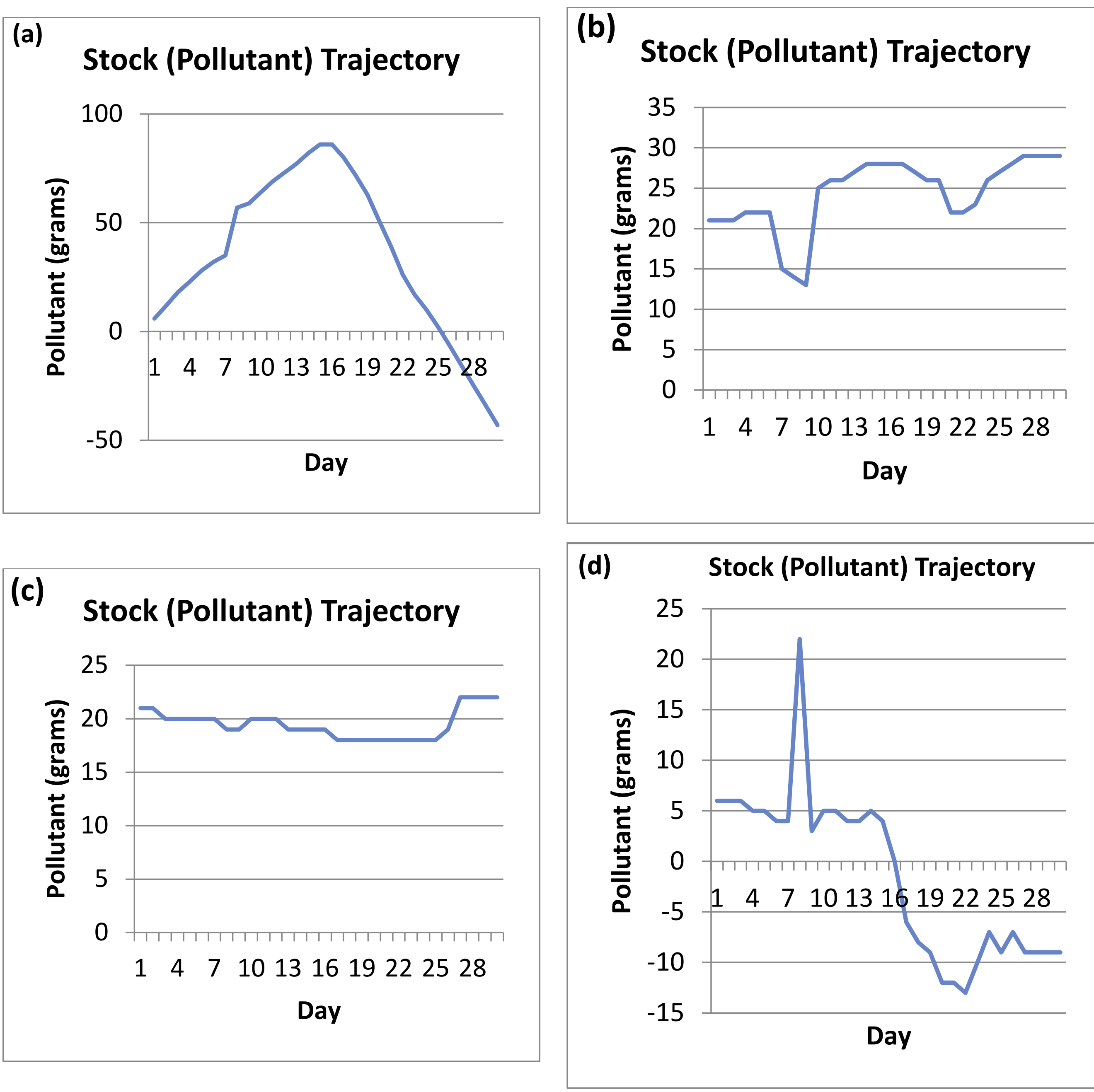

Fig. 3. (a): Correct answer. (b): A typical incorrcet response from G1. (c): A typical incorrcet response from G2. (d): A typical incorrcet response from G3.

90% had post-college supervisory and mid-level managerial experience).

On the pre-treatment test, subjects were asked simple accumulation questions (e.g. when was the most pollutant in the pond) (Stave et al., 2014), Task 1 **(T1)**, where information on pollutant inflow and outflow was provided in a graph (see Fig. 1, above). Although knowledge of environmental sciences, calculus or case analysis was not needed in this task, over 90% of these highly educated and well-experienced individuals did not carry out the task correctly. Even highly scientifically literate people (over 60%) in science, technology, engineering and mathematics (STEM) programs performed poorly on the CO_2 accumulation questions. Overall, they scored on T1 as: G1 = 2.03, G 2 = 2.09, and G3 = 2.06, out of possible 8 points. Groups did not differ in their performance on T1 (F (2, 96) = 0.08, p > 0.05). Fig. 3(a, b, c and d) shows the correct and typical incorrect responses of learners from all the three groups, G1, G2, and G3, on the question which requited them to draw the trajectory of the stock (pollutant).

Further analysis of these pefromances reveals that in all these three graphs (i.e., Fig. 3(b), 3(c) and 3(d)), subjects appear to use "coorelational heuristic (Cronin et al., 2009)" while doing task T1: in drawing the trajectory of polluant, while subjects in G1 and G2 coorelated with inflo (i.e., added pollutants") without accounting for the steep change during the period from Day 6 to Day 11, subjects in G3 followed the "net-flow" of pollutant pattern. None of them appears to track the trajectory of the popultant correctly. These results are in line with the earlier studies on the same (Stave et al., 2014) or similar tasks (Cronin et al., 2009; Erdas et al., 2015).

To test whether the two experimental groups who received facilitation differed in their reactions to this facilitation, a MANOVA was conducted using the two self-reported measures (Usefulness of Facilitation in Arousing Interest in the Task (FIT) and Usefulness of Facilitation in Understanding the Task (FUT)) as dependent measures. These perceptions of the users of (human or auto-scripted) facilitation were measured using a 5-point Likert scale. For example, facilitation was effective in arousing my interest in the task: Strongly agree (5), Agree (4), Undecided (3), Disagree (2), and Strongly disagree (1).

The MANOVA results indicated that treatment groups differed on the two measures, Wilk's $\lambda = .02$, F (2, 96) = 291, p < 0.005.

Based on separate MANOVAs, significant effects for the facilitation manipulation were found for FIT (p < 0.005) and FUT (p < 0.005). Post hoc comparisons indicated that FIT, the usefulness of facilitation in arousing interest in the task, assessed through Q. 10 listed in Table 4, was relatively high ((M (i.e., mean value) = 4.1)) in group G2, the human-facilitated group, than in group G3, auto-facilitated group, (M = 3.9). On the perceived utility of the facilitation, FUT, the G2 group rated the usefulness of facilitation in understanding the task, assessed through Q. 11, Q. 12, and Q. 13 listed in Table 4, in the very high (M ≥ 4.17 out of 5) followed by G3 group (M = 2.06). Participants of G1 were asked only about Question 14 given in Table 4 below. On this question of how effective this facilitated training was in raising the awareness of and engagement with environmental issues, all the three groups ranked it high on a 3-point Likert scale.

To test our hypotheses, all the subjects completed the post-treatment task, T2. A simultaneous look at Fig. 4 an Table 5 confirms all the three hypotheses: (i) *H1: subjects trained with human-facilitated SDILE perform better than those trained with auto-facilitated SDILE*, (ii) *H1a: Subjects trained with a standalone, automated SDILE perform better than those without any SDILE*, and (iii) *H1b: Subjects trained with a human-facilitated SDILE perform better than those without any SDILE.* When we look at the comparative performance (i.e., performance in T1 versus T2) of all the groups, as shown in Fig. 4, the group G2 appears to outperform the rest. In the absence of any SDILE based training, subjects in G1 did not show any significant improvement. Thus, it is safe to assume that effect of practice, if any, does not pose any threat to the validity of our main result: training with human-facilitated or auto-facilitated SDILE made the difference.

Table 4
Perceptions about learning and training with SDILEs.

Questions	G2 Responses (M)	G3 Responses (M)
User Interface: Using C-Learn is		
1. Fun	4.2	3.2
2. Pleasant	4.1	3.3
3. Exciting	4.2	3.5
4. Enjoyable	4.5	3.2
5. Is easy to use	5.0	3.8
6. Has user-friendly interface	4.5	4.0
7. Represents a real business situation	3.0	3.0
8. Has effective on-line help	4.5	4.2
9. Provides quick & useful feedback	4.5	4.2
Briefing: Facilitation was effective in		
10. Arousing my interest in the task	4.1	3.9
11. Helping me understand the task	3.5	3.3
Debriefing: Facilitation was effective in		
12. Clarifying misconceptions about the task	4.5	2.5
13. Encouraging me to reflect and learn	4.5	2.0
Engagement with environmental Issues:		
14. Participation in this experiment has increased my engagement with environmental issues	3	3

All the responses to the perceptions questions, except the response to question # 14, are on a 5-point Likert scale. For question number 14, we used a 3-point Likert scale: 3 (had increased), 2 (had no impact), and (1) decreased.

Table 5
Performance in T2 shows that all the hypotheses are supported.

Groups	Score: Mean (SD)	Test Statistic	Inference
G1	2.45 (2.12)	F(1, 64) = 213.39,	G2 performed better than G1
G2	8.00 (0.00)	p < 0.005	*(H1b is supported)*
G1	2.45 (2.12)	F(1,64) = 18.05, p < 0.005	G3 performed better than G1
G3	4.51 (2.15)		*(H1a is supported)*
G2	8.00 (0.00)	F(1, 64) = 86.51, p < 0.005	G2 performed better than G3
G3	4.51 (2.15)		*(H1 is supported)*

SD means standard deviation.

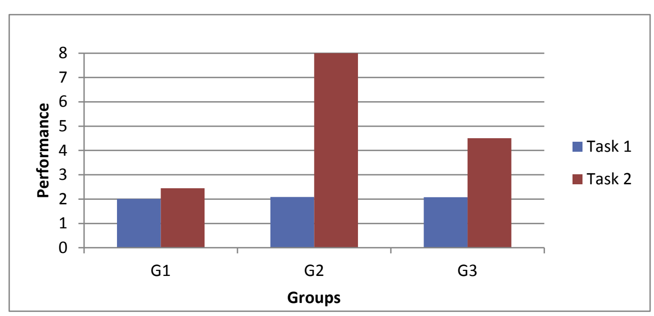

Fig. 4. Comparative group performance.

5. Discussions

Our main research question was: will the subjects trained with a human-facilitated SDILE better understand the dynamics of CO_2 accumulations than those trained with a standalone, automated SDILE?

We employed two measures to address this question. The first, an objective measure, was a two-part assessment: Part-(a) consisted of four-questions and part-(b) asked them to draw the trajectory (of pollutant). Four of the questions probed participants' understanding at the first and second levels of Bloom's taxonomy of education and training objectives (Bloom, 1956; Anderson and Krathwohl, 2001) (i.e., remembering and understanding). The other part-(b) question assessed participants' understanding at the third and fourth levels of Bloom's taxonomy (i.e., applying and analyzing). The second, a subjective measure, consisted of a self-reported questionnaire based on two, a 5-point and a 3-point, Likert scales. The questions on these two scales captured the subjects' perceptions about learning and training with SDILEs. Both the objective measures based assessment and the subjective questionnaire based responses did demonstrate some significant difference, favoring participants receiving training with facilitated SDILEs.

After training with facilitated SDILEs, individuals performed better on the CO_2 accumulations task; they were able to understand the difference between a stock and its flows and applied this knowledge correctly to trace the trajectory of CO_2 emissions accumulation over time. In fact, subjects who were trained with human-facilitated SDILEs understood and applied the stock and flow perspective with 100% accuracy. Not only did they answer the accumulation questions correctly but they were able to describe their reasoning in the written, descriptive part of the assessment. People who were trained with self-contained SDILE also showed an improved performance but not as much as those with human-facilitated SDILE. Those who carried out the task accurately, in their written descriptive answers, mentioned the use of “net flow” calculations while tracing the trajectory of CO_2 emissions. Thus, instead of focusing on either the inflow or the outflow alone, they simultaneously looked at both the flows - they applied the principle of accumulation correctly which enabled them to do the task correctly.

On this performance improvement on the CO_2 accumulation task, one could argue that it may not be the effect of training with SDILEs but the effect of problem solving practice. However, a post-hoc analysis of all the subjects' performances showed that the group with no SDILEs did not show any significant improvement (2.03 versus 2.45, $p > 0.05$) across the two trials while both groups with SDILEs demonstrated a remarkable improvement in their understanding of environmental accumulations - *training with SDILEs provided experiential learning that made the difference*. These findings are consistent with earlier studies where it was shown that practice alone is not sufficient but rather a better understanding of the task structure improves performance (Sterman, 2000; Qudrat-Ullah, 2014a).

The superior performance of subjects with human-facilitated SDILE over those with automated, standalone SDILE (i.e., the affirmative answer to main research question) can be attributed to their access to what Schön (1983) called “reflective conversation with the situation” during the human-facilitated debriefing session, which gave them greater adaptability in recognizing system changes and updating their mental models about the task system. Compared with the automated SDILE group, the subjects in the human-facilitated group had access to multiple and varied “solutions” (of their peers) with corrective feedback from the human facilitator, which lead to their better understanding of the environmental accumulation dynamics. Note that subjects trained with automated, standalone SDILE were successful in learning and understanding the CO2 accumulation task, at the first and second levels of Bloom's taxonomy of education and training stages, but did not succeed fully in the application of the learned knowledge (the third and fourth levels of Bloom's taxonomy). Therefore, to improve people's decision making in stock and flow oriented, accumulation tasks, the provision of human-facilitation in simulation-based training sessions appears to be critical.

On a more personal level, we asked the participants about the usefulness and utility of learning and training with SDILEs. Although subjects with human support were more excited and enthusiastic, both groups, G2 and G3, affirmed their positive reaction to the SDILEs-based intervention (see Table 5, question 10 to 13). The SDILE provided them with the opportunity to make decisions in a safe and unthreatening environment, receive immediate feedback and reflect and learn about the structure of the task system. The improved understating of the basic dynamics of environmental accumulations led to their improved performance. The development of stock and flow thinking (subjects understood the key principle that it is the net flow that causes any change in a stock), which represents a changed way of thinking, was the key benefit for them. Those without an access to SDILE could not experience the “structure drives behavior” phenomenon leading to their poor understanding of the basic dynamics of CO_2 accumulations.

Contrary to the majority of prior research on “accumulation tasks” which overwhelmingly focuses on “why people fail in grasping basics principles of accumulation”, this research has attempted to advance the debate towards “how people can better understand the basic dynamics of accumulation tasks”. By doing so, we have presented a relatively efficient and cheaper alternative in contrast to the formal, a semester or longer time based educational program: train people with human facilitated SDILES in a workshop setting. Business organizations both in the public and private sector can avail this low-cost solution by either developing an in-house capability (a trained facilitator is needed) or engaging a third-party training providers.

As the role of education and understanding of the issue is critical in engaging the public on any scientific topic or issue, learning and decision making in environmental emissions related tasks should be of help. Specifically, we were interested to know to what extent our participants were influenced by this scientific activity on their awareness of and engagement with environmental issues. When asked (see question # 20 in Table 3), over 96% of subjects responded, “Participation in this experiment has increased our engagement with environmental issues.” This is very encouraging news for those who are trying hard to spread the virtues of the stock and flow perspective with the hope to increase public understanding of global warming and climate related issues. IPPC has been advocating long for public awareness and understanding about the environmental issues as a pre-requite for any successful strategies for the adaptation and mitigation of environmental issues (IPPC, 2007).

6. Conclusions

The original contribution of this study to the body of knowledge in the area of ILEs is towards the improved design of an ILE: our results show that when the objective is to educate and train people in dynamic tasks, traditional, automated, standalone design of an ILE is not sufficient. Instead, one has to explicitly incorporate the human-facilitation into the design of ILE, where the structure-behavior graphs of central variables of the task systems are presented and elaborated.

Based on the findings of this study, several important conclusions can be drawn:

- Learning and performance in dynamic tasks, such as the management of CO_2 emissions accumulation task, can be enhanced through training with SDILEs

- Subjects' training with a human-facilitated SDILE is more effective than training with an automated, standalone SDILE for CO_2 emissions accumulation type of tasks.
- It appears that the availability of human-facilitated debriefing session, a post-simulation-task facilitation where subjects were able to share and reflect on their performances (e.g., in comparison with their peers and the model solutions), made the difference - *subjects with the human-facilitated debriefing aid learned and applied the environmental accumulation principle accurately.*
- As indicated by self-reports, participants provided with human-facilitated SDILEs were more motivated and understood the task better than those with automated, standalone SDILEs. These results provide evidence that the improved performance of the participants on the environmental accumulation task was due to the availability of human-facilitated SDILE session. This reduces the likelihood of a potential alternative explanation that it was simply the provision of more information (in fact those in G1 had a 2-h interactive lecture on the topic but performed poorly), as opposed to specific human-facilitated debriefing aid, that caused the subjects to learn and apply stock and flow perspective effectively.
- Our results suggest that instead of asking people to become experts in system dynamics methodology per se through formal college/university course(s), training with human-facilitated SDILEs, in a workshop setting, can impart the basic but essential learning about the principle of accumulation — a low-cost solution to the important managerial need.

Overall, the general public plays a fundamental role in shaping public policies To gain a broader public support for pro-environmental initiatives, not only do we need scientifically literate people but also those who have knowledge on the basic dynamics (i.e. the stock and flow nature) of environmental issues. Therefore, for better understanding and management of global warming and climate change challenges, including CO_2's unabated accumulations, while certainly not sufficient, a whole-hearted embracing of the stock and flow perspective appears to be the way to go.

As the literature on “reduction of CO_2 emissions” suggests that the basic understating of the environmental accumulation processes can help decision makers to make better decisions for the management of environmental emissions in their organizations. As per the results of this study, education and training with relatively low-cost, human-facilitated SDILEs appears to be an efficient choice.

To support the diffusion of sustainable development in universities curricula (Lozano, 2006, 2010), it is reasonable to expect that the adaptation of the stock and flow perspective by the education and training sector of the economy might help. For instance, educators, both at the undergraduate and graduate level, can encourage the development and use of human-facilitated SDILEs in their courses at appropriate levels in their curricula-enhancing decision makers' ability to better deal with complex, dynamic tasks such as the management of environmental emissions accumulation tasks. Consequently, such experiential and transformative learning is expected to support the design and implementation of mitigation and adaptation strategies for climate change.

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